

IML

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Data and Model

Fit the model on Boston housing dataset to predict the median values

```
data("Boston", package = "MASS")
head(Boston)

##      crim zn indus chas   nox    rm  age    dis rad tax ptratio  black
## 1 0.00632 18  2.31    0 0.538 6.575 65.2 4.0900   1 296    15.3 396.90
## 2 0.02731  0  7.07    0 0.469 6.421 78.9 4.9671   2 242    17.8 396.90
## 3 0.02729  0  7.07    0 0.469 7.185 61.1 4.9671   2 242    17.8 392.83
## 4 0.03237  0  2.18    0 0.458 6.998 45.8 6.0622   3 222    18.7 394.63
## 5 0.06905  0  2.18    0 0.458 7.147 54.2 6.0622   3 222    18.7 396.90
## 6 0.02985  0  2.18    0 0.458 6.430 58.7 6.0622   3 222    18.7 394.12
##   lstat medv
## 1  4.98 24.0
## 2  9.14 21.6
## 3  4.03 34.7
## 4  2.94 33.4
## 5  5.33 36.2
## 6  5.21 28.7

#install.packages("iml")
#library("randomForest")
library("iml")
library("randomForest")

## randomForest 4.6-12

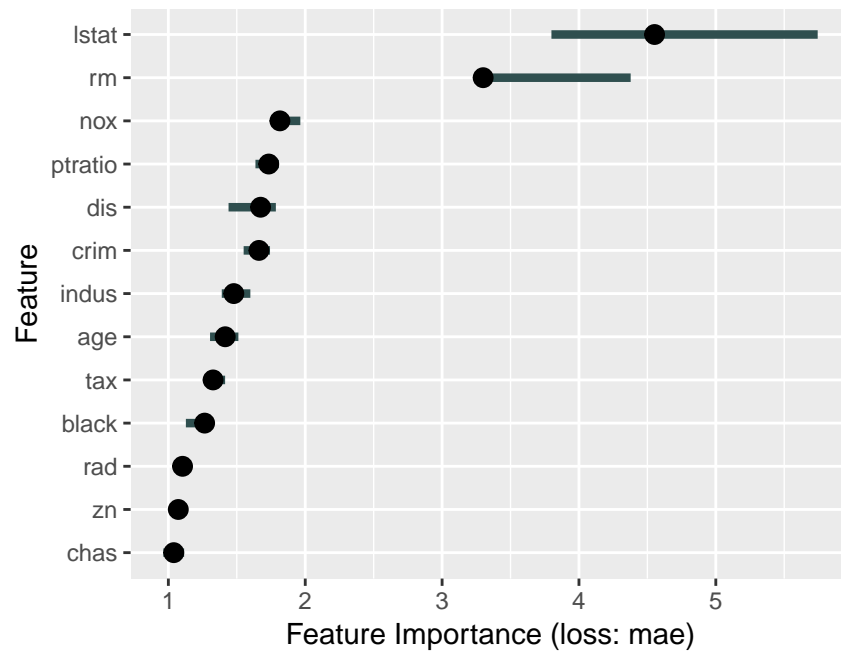
## Type rfNews() to see new features/changes/bug fixes.

set.seed(2019)
rf = randomForest(medv ~ ., data = Boston, ntree = 1000, mtry = 4)

X = Boston[which(names(Boston) != "medv")]
predictor = Predictor$new(rf, data = X, y = Boston$medv)
```

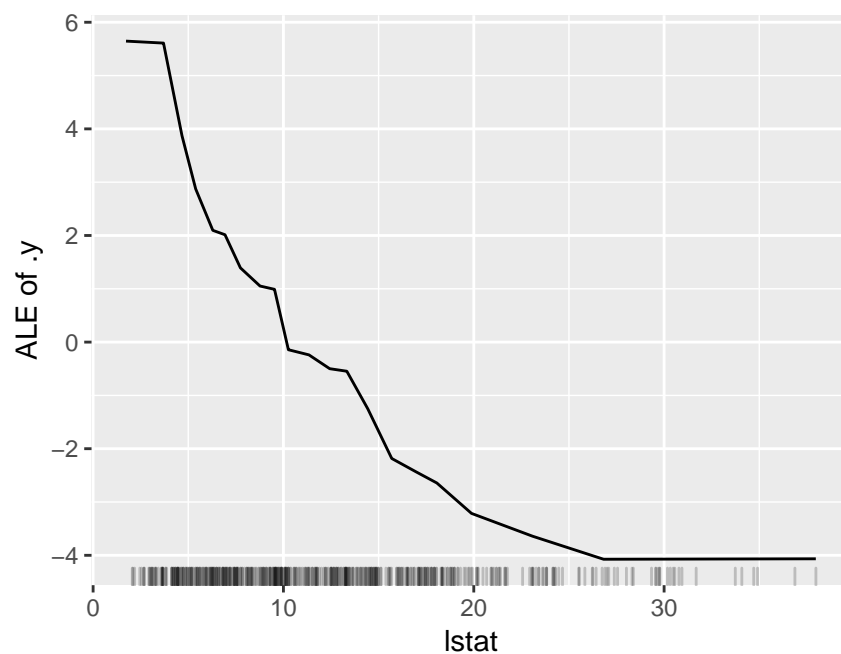
Feature importance obtained by the permutation algorithm

```
imp = FeatureImp$new(predictor, loss = "mae")
plot(imp)
```

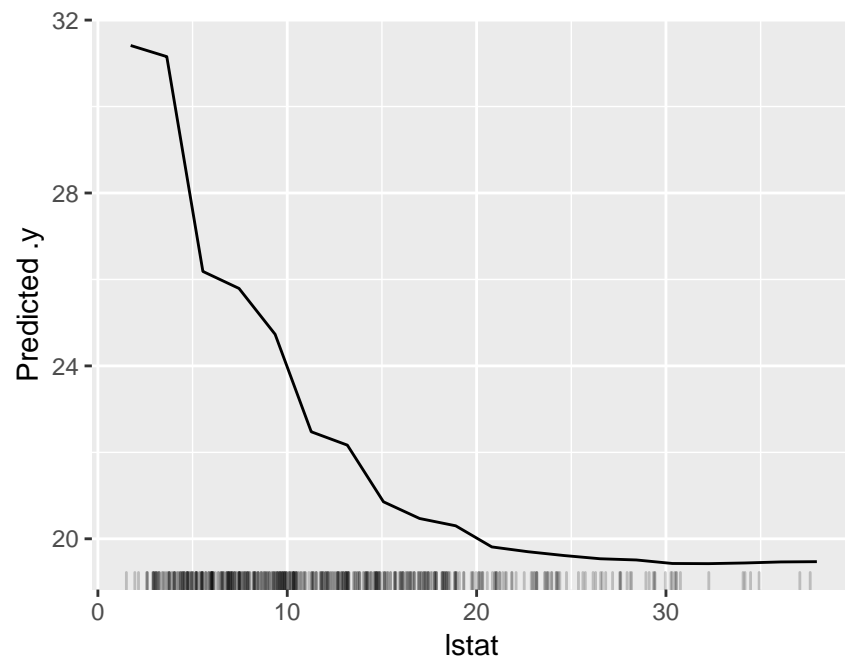


Feature effects (ALE or PDP)

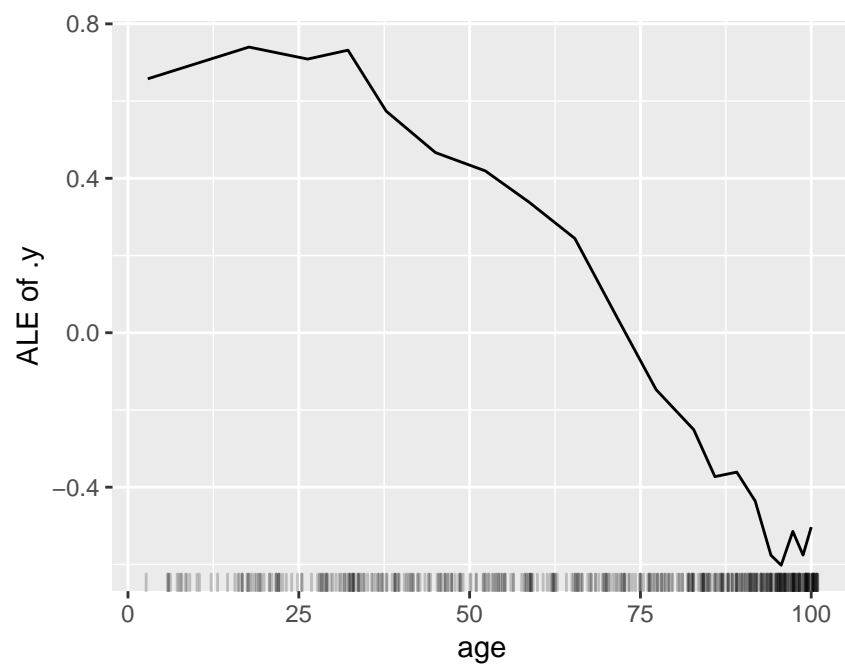
```
ale = FeatureEffect$new(predictor, feature = "lstat", method = "ale", grid.size = 20)
ale$plot()
```



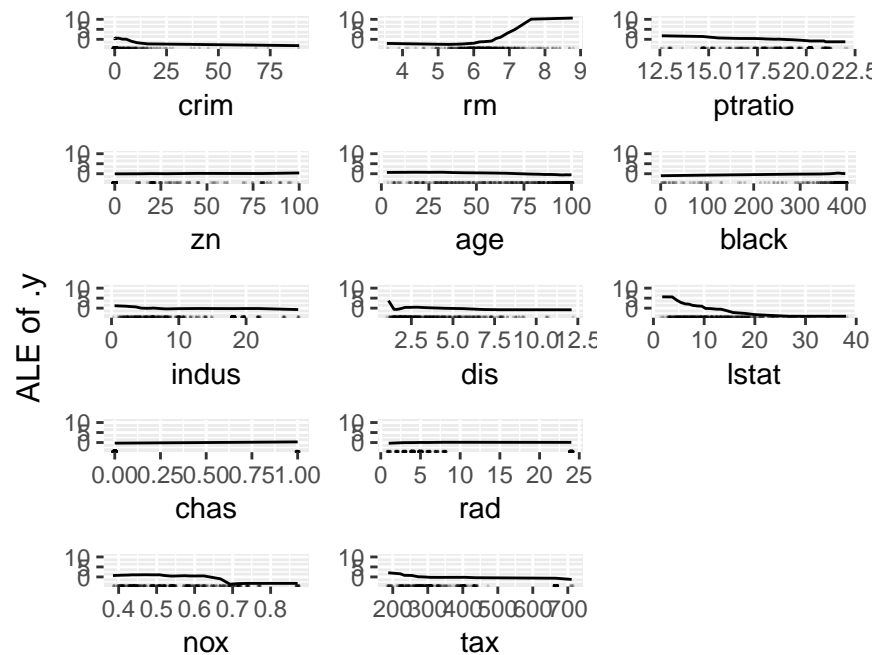
```
pdp = FeatureEffect$new(predictor, feature = "lstat", method = "pdp", grid.size = 20)
pdp$plot()
```



```
ale$set.feature("age")
ale$plot()
```

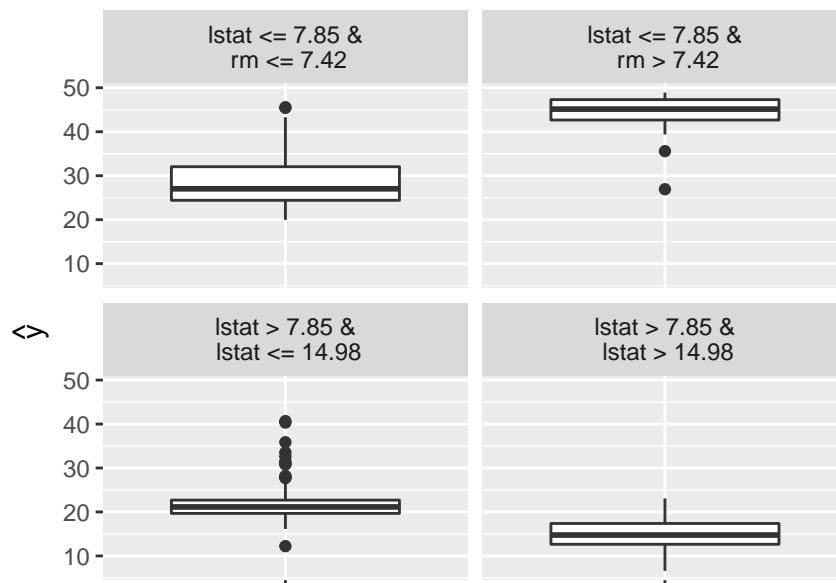


```
effs = FeatureEffects$new(predictor)
plot(effs)
```

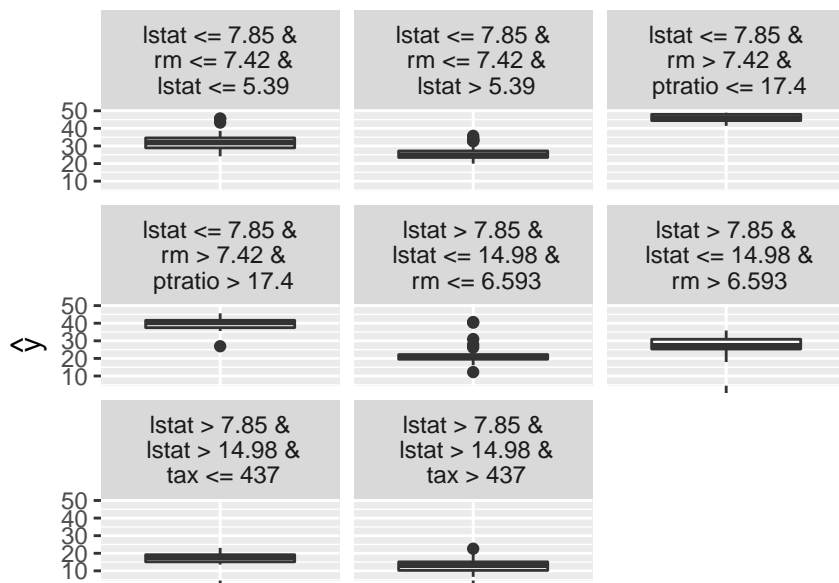


Global Surrogate Model (Tree-based)

```
tree_sur = TreeSurrogate$new(predictor,maxdepth = 2)
plot(tree_sur)
```



```
tree_sur = TreeSurrogate$new(predictor,maxdepth = 3)
plot(tree_sur)
```



Local Surrogate Model

LocalModel fits locally weighted linear regression models to explain the individual predictions.

```
loc = LocalModel$new(predictor, X[1,], k = 5)
```

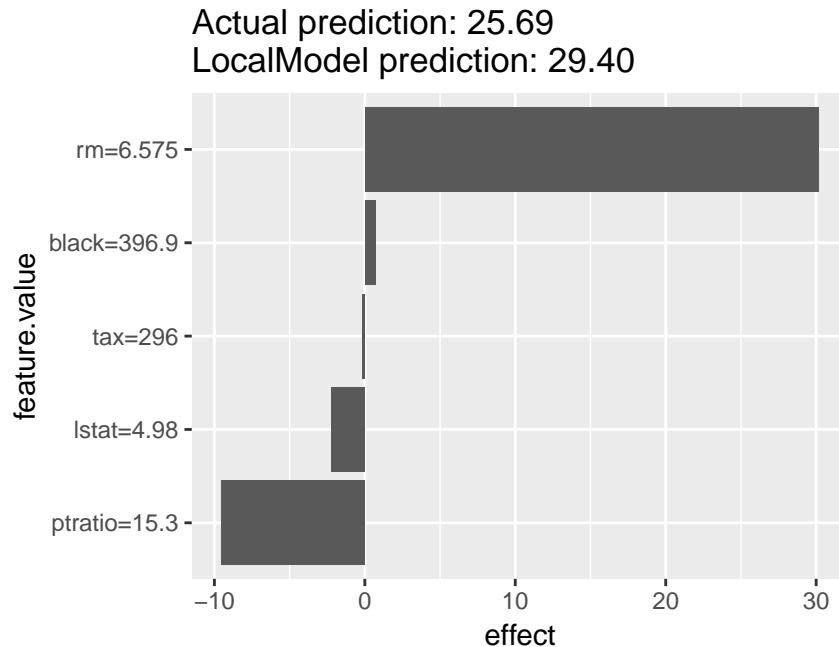
```
## Loading required package: glmnet
## Loading required package: Matrix
## Loading required package: foreach
## Loaded glmnet 2.0-13
## Loading required package: gower
```

```
print(loc)
```

```
## Interpretation method: LocalModel
##
##
## Analysed predictor:
## Prediction task: unknown
##
##
## Analysed data:
## Sampling from data.frame with 506 rows and 13 columns.
##
## Head of results:
##          beta x.recoded    effect x.original feature feature.value
## rm      4.58700691    6.575 30.1595704    6.575    rm      rm=6.575
## tax     -0.00049118   296.000 -0.1453893    296     tax      tax=296
## ptratio -0.62226762   15.300 -9.5206946    15.3  ptratio  ptratio=15.3
## black    0.00180294   396.900  0.7155868    396.9  black   black=396.9
```

```
## lstat -0.44052418 4.980 -2.1938104 4.98 lstat lstat=4.98
```

```
plot(loc)
```



Shapley Value

The contribution of a feature value to the difference between the actual prediction and the mean prediction

```
shapley = Shapley$new(predictor, X[1,])
print(shapley)
```

```
## Interpretation method: Shapley
## Predicted value: 25.694383, Average prediction: 22.529530 (diff = 3.164854)
##
## Analysed predictor:
## Prediction task: unknown
##
##
## Analysed data:
## Sampling from data.frame with 506 rows and 13 columns.
##
## Head of results:
##   feature      phi      phi.var feature.value
## 1   crim -0.34601096 0.898376575   crim=0.00632
## 2    zn  0.02567896 0.011977925     zn=18
## 3   indus 0.60867790 0.584654669   indus=2.31
## 4    chas -0.01097749 0.005363373     chas=0
## 5    nox -0.27072254 0.823207605   nox=0.538
## 6     rm -1.30087850 26.643823742     rm=6.575
```

```
plot(shapley)
```

Actual prediction: 25.69
Average prediction: 22.53

